A two-level optimization based learning control strategy for wet clutches

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Abstract: This paper proposes a two-level control strategy for wet clutches. On the low level, the control signal is calculated by solving a constrained optimal control problem. On the high level, the measured responses are used to update the system models and constraints that are used in the optimization for the next control signal. In this way a learning algorithm is obtained, which is able to optimize the control signal during normal operation, despite its complex and time-varying dynamic behavior, and without requiring long calibrations or complex models. The performance and robustness of this control scheme are validated on an experimental test setup.

Keywords: recursive estimation, identification, optimal control, learning control, iterative methods, time-varying systems, wet clutch, control system design, ride comfort

1. INTRODUCTION

Wet clutches, schematically drawn in figure 1, are devices commonly used in automatic transmissions for off-highway vehicles and agricultural machines to transfer torque from the engine to the load. To engage a clutch, current is sent to a servovalve, forcing a hydraulic piston to press two sets of friction plates together, connected respectively the to input and output shaft. During the first part of the engagement process, referred to as the filling phase, pressure builds up, causing the line and clutch chamber to fill up with oil. When the pressure is high enough to overcome the return spring force, the piston advances towards the plates but no torque is transferred yet. The slip phase begins once the piston reaches the plates. Then torque transfer starts, causing the difference in rotational speeds between the shafts to decrease until they rotate synchronously. Operators expect such engagements to occur with as little delay as possible, and without vibrations. This can be realized by a short filling phase such that torque transfer commences as soon as possible, followed by a smooth transition into the slip phase ensuring torque peaks are avoided.

Modeling a clutch is difficult due to the complex, non-linear behavior, which changes when the piston comes into contact with the plates and varies over time with the operating conditions such as the load and the oil temperature, but also due to wear. Nevertheless, extensive, physical models have been developed (Lucente et al., 2007) as well as several models

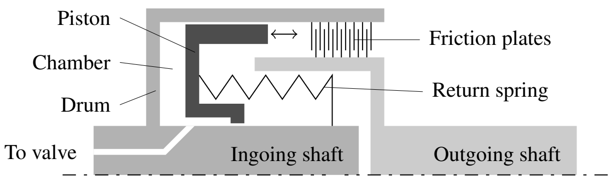

Fig. 1. Cross-section of a wet clutch and its components

with the purpose of controller design. A model-inversion technique is used for feedforward control in (Horn et al., 2003), while the feedforward signal in (Haj-Fraj and Pfeiffer, 2001) is found by solving an optimal control problem. Various types of non-linear feedback controllers have also been developed, (Morselli et al., 2003; Montanari et al., 2004; Glielmo et al., 2004). To reduce the required modeling effort, iterative learning control (ILC, (Bristow et al., 2006)) is employed in (Pinte et al., 2010) to compensate the large uncertainty. Another difficulty consist of the piston position sensors that are employed by most of the controllers discussed above, but which are not available for the considered application. The time-variable dynamics, which make robust wet clutch control a challenging problem (Sun and Hebbale, 2005), then become even more of an issue, as the piston behavior depends strongly on the oil viscosity and hence on the temperature. The industrial solution consists of using parameterized feedforward signals that are regularly recalibrated. To avoid the resulting downtime, various patents have been claimed to derive empirical rules for adjusting the signal parameters during normal machine operation, based on observations of past engagements (Berger and Pollack, 1994; Hebbale and McCulloch, 1994). No systematic framework is available however.

In this paper a control strategy is proposed focusing only on the filling phase and the transition into the slip phase, thus avoiding the need for accurate slip phase models [1]. The

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[1] Control signal optimization for the entire process is under development.

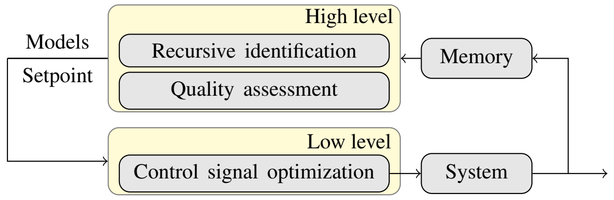

Fig. 2. Presented control scheme: After each engagement the model and constraints for the optimization problem are updated and the next control signal is optimized.

aim is to minimize the duration of the filling phase while ensuring a smooth transition into the slip phase. To develop a robust controller that achieves this without requiring complex models and without position measurements, learning control is introduced. However, techniques like ILC are difficult to use, as they aim at improving tracking of a measurable signal, and would require a suitable reference pressure. The problem would then be tackled indirectly, as the optimal pressure reference has to be learned as well. Instead, this paper proposes to find the control signals directly by solving an optimal control problem, such that the goal of minimizing the duration can be included directly, and which also allows constraints to be taken into account explicitly. Learning is then included by adding a second level to the controller, as illustrated in figure 2, consisting of (i) a recursive identification algorithm to supply models adapted to the operating conditions and (ii) a learning law to update the endpoint constraints based on an assessment of the observed engagement quality.

The rest of this paper is organized as follows. Sections 2 and 3 discuss the low and high-level controllers respectively. Section 4 discusses the experimental validation of the developed control strategy. Finally, section 5 presents some conclusions and suggestions for future research.

2. LOW LEVEL: CONTROL SIGNAL OPTIMIZATION

In between engagements, the low level controller finds the next control signal by solving a numerical optimization problem. This signal encompasses the filling phase and the transition into the slip phase. The final value of this signal is then maintained during the rest of the engagement, leading to control signals as illustrated in figure 3. The optimization problem minimizes the length of the first part in order to complete the filling phase as soon as possible. As the optimization problem is solved in discrete time, this corresponds to minimizing the number of samples K in the optimized control signal. To ensure a gentle transition into the slip phase without torque spikes, constraints are added to ensure the piston reaches the plates at sample $K-N2$ and to limit the piston velocity in an interval $[K-N_1 K-N_2]$ before that. Afterwards, between $K-N_2$ and K, the piston remains in contact with the plates, but the pressure increases as an end-point constraint is added on the pressure at sample K, such that an appropriate level of torque is obtained when the filling phase is completed. The values of N_1 and N_2 have been obtained experimentally, but remain fixed once the controller is started. To impose these constraints, models for both pressure and position are needed. These models are supplied by the high-level controller, and are discussed further on.

Minimizing K is a non-convex problem, so it is reformulated using a bisection algorithm (Boyd and Vandenberghe,

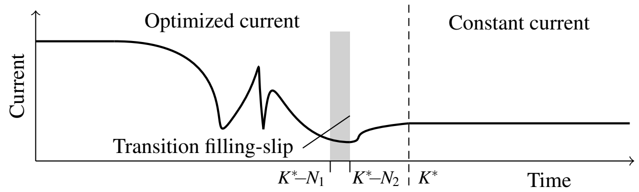

Fig. 3. Composition of control signals: Optimized part for filling phase and smooth transition into slip phase, followed by a constant part maintaining the last optimized value.

2004). Convex feasibility problems with fixed values of K are then solved until the lowest value K^* and the corresponding control signal are found. Since only integer values of K are allowed, many feasible solutions might exist for K^*. To ensure the smoothest control signal is obtained, L_1-regularization is added, resulting in feasibility problems given by

$$\min_{u(:),x(:)} \sum_{k=0}^{K-2} \frac{|u(k+1)-u(k)|}{T_s}, \tag{1a}$$

$$\begin{aligned}
\text{s.t.} \quad & x(0) = \overline{x0}, && \text{(1b)}\\
& x(k+1) = Ax(k)+Bu(k), \quad k=0,\dots K-2, && \text{(1c)}\\
& \begin{pmatrix} p(k) \\ z(k) \end{pmatrix} = Cx(k)+Du(k), \quad k=0,\dots K-1, && \text{(1d)}\\
& z(k+1)-z(k) < \varepsilon T_s, \quad k=K-N_1,\dots K-N_2, && \text{(1e)}\\
& z(K-N_2) = z_{final}, && \text{(1f)}\\
& p(K-1) = p_{final}, && \text{(1g)}\\
& u_{lb} < u(k) < u_{ub}, && \text{(1h)}\\
& y_{lb} < Cx(k)+Du(k) < y_{ub}, && \text{(1i)}\\
& \qquad \text{for } k=0,\dots K-1,
\end{aligned}$$

with (1a) the L_1-regularization on the control signal u. Eqs (1b) up to (1d) represent the initial conditions and dynamic behavior of the clutch, relating the input current u to the output pressure p and piston position z. Next, eqs (1e) and (1f) correspond to the constraints on the piston position between $K-N_1$ and $K-N_2$, with the piston reaching the plates at $K-N_2$. The endpoint constraint on the pressure is given next, by (1g). Finally, (1h) and (1i) put bounds on the servovalve current, pressure and piston position.

3. HIGH LEVEL: MODEL AND SETPOINT LEARNING

This section describes the algorithms for the high-level learning of the models and setpoints needed by the optimization problem. First, the recursive identification of the pressure model is discussed in 3.1, followed by the algorithm for updating the position model in 3.2. The learning of the pressure setpoint is discussed next, in 3.3.

3.1 Recursive identification of pressure model

The low-level optimization problem requires a model relating the servovalve current to the pressure. Pressure measurements in the line to the clutch are readily available in industrial transmissions, so these can be used to identify a model for the filling phase. A recursive technique is developed, which offers the possibility to improve the model accuracy and to compensate for slowly varying dynamics by combining information from multiple engagements. Since only the filling phase needs to be modeled, a linear, low order, discrete-time model is used. Because the behavior is considered time-invariant over the span of a single engagement, the model parameters are updated once after each engagement, using the complete batch of measured data. This differs from the traditional recursive estimation techniques where updates are calculated after each sample (Ljung, 1998). Once the model parameters are estimated, the matrices A, B, C and D of the state-space model (1) are updated accordingly. The recursive estimation algorithm will first be derived, before its relation to other recursive estimators is briefly discussed.

The system is modeled as a discrete-time output error model (Ljung, 1998), with dynamics described by [2]

$$y(k) = \frac{B(q^{-1},\theta)}{F(q^{-1},\theta)}u(k-n_k)+e(k), \tag{2}$$

where $u(k)$ and $y(k)$ are the input (current) and output (pressure) respectively, $e(k)$ is measurement noise and n_k is the number of delays. The delay operator is denoted by q^{-1}, and

$$B(q^{-1},\theta) = b_1+b_2q^{-1}+\ldots+b_{n_b}q^{-n_b}, \tag{3}$$

$$F(q^{-1},\theta) = 1+f_1q^{-1}+\ldots+f_{n_f}q^{-n_f} \tag{4}$$

are polynomials of q^{-1} that depend on the parameter vector $\theta = [b_1\, b_2\, \ldots\, b_{n_b}\; f_1\, f_2\, \ldots\, f_{n_f}]^T$.

First, consider only a **single batch** of measured data $\mathbf{y} = [y(1)\, y(2)\, \ldots\, y(N)]^T$ and $\mathbf{u} = [u(1)\, u(2)\, \ldots\, u(N)]^T$. For the given model structure, the output can be predicted as

$$\hat{y}(k|\theta) = \frac{B(q^{-1},\theta)}{F(q^{-1},\theta)}u(k-n_k) = \varphi(k,\theta)^T\theta, \tag{5}$$

where $\varphi(k,\theta)$ is defined as

$$\begin{aligned}\varphi(k,\theta) = [&u(k-n_k) \quad u(k-n_k-1)\ \ldots\ u(k-n_k-n_b+1)\\ &-\hat{y}(k-1|\theta)\ -\hat{y}(k-2|\theta)\ \ldots -\hat{y}(k-n_f|\theta)]^T.\end{aligned} \tag{6}$$

An estimate for the system parameters can now be found in the weighted least squares sense as

$$\theta^* = \underset{\theta\in D_{\mathscr{M}}}{\arg\min}\, (\mathbf{y}-\Phi(\theta)^T\theta)^T\mathbf{W}(\mathbf{y}-\Phi(\theta)^T\theta), \tag{7}$$

where $\mathbf{W}$ is a positive definite weighting matrix, $\Phi(\theta) = [\varphi(1,\theta)\, \varphi(2,\theta)\ldots\varphi(N,\theta)]$ and $D_{\mathscr{M}}$ is the set of stable models. This non-linear, non-convex least squares problem can be solved as a sequential quadratic program (SQP)(Nocedal and Wright, 2006). In this SQP, (7) is approximated at the current estimate $\hat{\theta}$ by considering $\Phi(\theta)$ fixed and independent of θ, denoted by $\Phi_{\hat{\theta}}$. Next, a new estimate $\hat{\theta}+\alpha\,\delta\hat{\theta}$ is calculated, where $\delta\hat{\theta}$ is the update direction given by

$$\delta\hat{\theta} = \underset{\delta\theta}{\arg\min}\ \left(\mathbf{y}-\Phi_{\hat{\theta}}^T(\hat{\theta}+\delta\theta)\right)^T\mathbf{W}\left(\mathbf{y}-\Phi_{\hat{\theta}}^T(\hat{\theta}+\delta\theta),\right) \tag{8}$$

$$= \underset{\delta\theta}{\arg\min}\ \delta\theta^T\Phi_{\hat{\theta}}\mathbf{W}\Phi_{\hat{\theta}}^T\delta\theta - 2\delta\theta^T\Phi_{\hat{\theta}}\mathbf{W}(\mathbf{y}-\Phi_{\hat{\theta}}^T\hat{\theta}), \tag{9}$$

$$= (\Phi_{\hat{\theta}}\mathbf{W}\Phi_{\hat{\theta}}^T)^{-1}\Phi_{\hat{\theta}}\mathbf{W}(\mathbf{y}-\Phi_{\hat{\theta}}^T\hat{\theta}), \tag{10}$$

and α is a scalar step size selected using backtracking [3]. This iterative estimation process is repeated by calculating new estimates for $\hat{\theta}+\alpha\delta\hat{\theta}$, each time recalculating $\Phi_{\hat{\theta}+t\delta\hat{\theta}}$, until it converges and the solution is found. These SQP's guarantee convergence towards a local minimum, so to ensure the global optimum is found it is essential to supply a good initial estimate(Nocedal and Wright, 2006). In the considered recursive case, good initial estimates can be found by selecting the models estimated after the previous engagement. As the SQP converges, the updates $\delta\hat{\theta}$ converge to 0 and so does $\Phi_{\hat{\theta}}\mathbf{W}(\mathbf{y}-\Phi_{\hat{\theta}}^T\hat{\theta})$ in (10). As a result, around the optimal solution, this term can be neglected and the cost function in (9) can be approximated using only the quadratic term.

Denote this first batch as i, with for example $\mathbf{y_i}$ and $\hat{\mathbf{y}}_\mathbf{i}$ vectors of the measured and predicted outputs. When adding a **a second batch** of data, $i+1$, the estimation problem yields

$$\begin{aligned}\hat{\theta}_{i+1} = \underset{\theta\in D_{\mathscr{M}}}{\arg\min}\, &(\mathbf{y}_{i+1}-\hat{\mathbf{y}}_{\mathbf{i+1}}(\theta))^T\mathbf{W}(\mathbf{y}_{i+1}-\hat{\mathbf{y}}_{\mathbf{i+1}}(\theta))\\ &+(\mathbf{y}_i-\hat{\mathbf{y}}_\mathbf{i}(\theta))^T\mathbf{W}(\mathbf{y}_i-\hat{\mathbf{y}}_\mathbf{i}(\theta)).\end{aligned} \tag{11}$$

In this equation, $\hat{\theta}_{i+1}$ is the estimate for θ, made after the $(i+1)$-th batch is added and using data from batches i and $i+1$. The second term in this equation is the same as (7), and can thus be approximated by its quadratic approximation when a model $\hat{\theta}_i$ for the first batch is known. Substituting the first term of (9) into (11) and using the notation $\mathbf{H}_i = \Phi_{\hat{\theta}_i}\mathbf{W}\Phi_{\hat{\theta}_i}^T$, yields

$$\begin{aligned}\hat{\theta}_{i+1} = \underset{\theta\in D_{\mathscr{M}}}{\arg\min}&(\mathbf{y}_{i+1}-\hat{\mathbf{y}}_{\mathbf{i+1}}(\theta))^T\mathbf{W}(\mathbf{y}_{i+1}-\hat{\mathbf{y}}_{\mathbf{i+1}}(\theta))\\ &+(\theta-\hat{\theta}_i)^T\mathbf{H}_i(\theta-\hat{\theta}_i),\end{aligned} \tag{12}$$

which is again a non-convex, non-linear least squares problem. Using a similar SQP approach, the update direction for a current estimate $\hat{\theta}$ is given by

$$\begin{aligned}\delta\hat{\theta} = \underset{\delta\theta}{\arg\min}\ &\delta\theta^T(\Phi_{\hat{\theta}}\mathbf{W}\Phi_{\hat{\theta}}^T+\mathbf{H}_i)\delta\theta\\ &-2\delta\theta^T\left(\Phi_{\hat{\theta}}\mathbf{W}(\mathbf{y}-\Phi_{\hat{\theta}}^T\hat{\theta})-\mathbf{H}_i(\hat{\theta}-\hat{\theta}_i)\right),\end{aligned} \tag{13}$$

$$\delta\hat{\theta} = (\Phi_{\hat{\theta}}\mathbf{W}\Phi_{\hat{\theta}}^T+\mathbf{H}_i)^{-1}\left(\Phi_{\hat{\theta}}\mathbf{W}(\mathbf{y}-\Phi_{\hat{\theta}}^T\hat{\theta})-\mathbf{H}_i(\hat{\theta}-\hat{\theta}_i)\right). \tag{14}$$

When this SQP is solved the series of $\delta\hat{\theta}$ again converges to 0, and so does

$$\Phi_{\hat{\theta}}\mathbf{W}(\mathbf{y}_{i+1}-\Phi_{\hat{\theta}}^T\hat{\theta})-\mathbf{H}_i(\hat{\theta}-\hat{\theta}_i) \to 0. \tag{15}$$

Once the optimal solution is found, the cost function for the 2 batches can thus approximated by the first, quadratic, term in (13). When a third batch of data is added, the new estimate can be found in the same way as in (12), requiring only $\mathbf{H}_{i+1} = \Phi_{\hat{\theta}_{i+1}}\mathbf{W}\Phi_{\hat{\theta}_{i+1}}^T+\mathbf{H}_i$ and the model $\hat{\theta}_{i+1}$ from the first two batches. Based on this reasoning, a recursive estimation algorithm can thus be derived, which consists of solving the SQP (12) each time a batch of data becomes available, and storing $\mathbf{H}$ and $\hat{\theta}$ for future calculations. A minor modification is still needed when the system behavior varies with time: Past data is weighted with a forgetting factor, which is realized by multiplying the second term in (12) with a positive scalar < 1.

The derived algorithm can be compared to the standard recursive least squares estimator (Ljung, 1998), when it calculates an estimate after a batch instead of after each data sample. The standard recursive least squares estimator then only performs one iteration each time a new batch of data becomes available, while the presented SQP approach performs several iterations until convergence is obtained. Using the SQP to solve several iterations for each batch is justified as it increases the convergence speed, and sufficient computational time is available in between engagements.

[2] The notation of (Ljung, 1998) will be used throughout this section.

[3] The normal backtracking algorithm (Nocedal and Wright, 2006) is adapted to make sure that the model remains stable, reducing the step size until either the model is stable or the step size becomes too small and the SQP is stoppped.

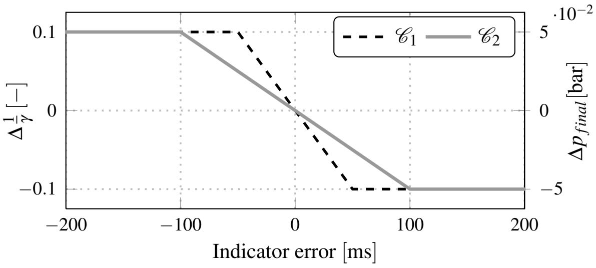

Fig. 4. High-level learning of position model and pressure setpoint, based on $t^*_{start} - t_{start}$ and $t^*_{sync} - t_{sync}$ respectively.

3.2 Iterative learning of position model

The recursive estimation technique derived in section 3.1 provides the optimization procedure (1) with a model for predicting the pressure inside the clutch. A model for the piston position is also required such that constraints on the piston movement and velocity can be imposed. Unfortunately, no position sensor is available so a comparison between the measured and predicted position can not be made, and hence a recursive identification algorithm similar to that of section 3.1 can not be applied. It is however possible to estimate the time when the piston makes contact with the plates, based on changes in the measured rotational speeds when torque transfer starts. This value t_{start} can then be compared with the predicted contact time, $t^*_{start} = (K^* - N_2) * T_s$. Based on the difference between the two, the position model is updated to better correspond with the measured behavior, and is inserted into (1) before calculating the next control signal. When the model has been updated such that it manages to predict the contact time accurately, the constraints on the piston velocity and displacement result in the desired smooth transitions between the filling to slip phases.

In this paper, a first order model is used as a crude approximation of the relation between pressure and piston position. The force equilibrium for the piston, considering only a linear spring, viscous oil forces and the hydrostatic force, results in

$$\frac{z(s)}{p(s)} = \frac{A}{cs+K}, \tag{16}$$

with A, K and c the surface area of the piston in the clutch chamber, the linearized spring stiffness and the viscous friction constant respectively, and s denoting the Laplace variable. Since it is not the goal to estimate an accurate physical model, and in order to simplify the recursive identification, it is replaced by the following model with the same structure

$$\frac{z(s)}{p(s)} = \gamma\frac{1}{s+2\pi}, \tag{17}$$

where the pole is fixed at $1Hz$, an estimate which is based on measurements performed on a similar test setup equipped with a piston position sensor. Hence, the resulting model contains only one unknown parameter γ, and γ can be chosen such that the predicted position reaches z_{final} at the measured contact time t_{start}. In order to get good predictions under all conditions, the following iterative update-law based on the difference between t_{start} and t^*_{start} is implemented:

$$\frac{1}{\gamma_{i+1}} = \frac{1}{\gamma_i} + \mathscr{C}_1(t^*_{start} - t_{start}), \tag{18}$$

where $\mathscr{C}_1$ is a saturated proportional controller, shown in figure 4. Equation (18) is an ILC-type learning law that updates the value of γ, such that the predicted contact time becomes more accurate. $1/\gamma$ is updated instead of γ because it can easily be interpreted as a measure for the travel distance.

Over a short period of time, wear can be neglected and the travel distance for the piston remains constant. γ then only captures neglected dynamics, but does change over time due to the oil viscosity depending on the temperature. Over a longer period of time, wear comes into play and γ compensates for changes in the dynamics as well as the travel distance. Thus, z_{final} in (1g) can be chosen freely, in this case it is fixed at 1.

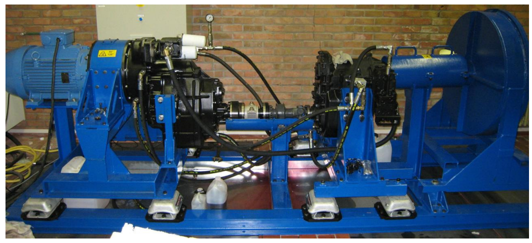

Fig. 5. Test setup: (from left to right) motor, controlled transmission, torque sensor, brake transmission and flywheel.

3.3 Iterative learning of pressure setpoint

When the pressure and position models predict the system behavior sufficiently accurate, the optimized control signal gently brings the piston into contact with the plates at the end of the filling phase. After this, constraint (1g) ensures that the pressure is increased to p_{final}, and kept constant for the remainder of the engagement resulting in a linear acceleration of the load. The acceleration time required before ingoing and outgoing shafts rotate synchronously depends inversely on the transferred torque and hence the pressure p_{final} pressing the plates together. In this paper the goal is have both shafts rotating synchronously, $1s$ after torque transfer commences. To this end, the high-level controller learns the value p_{final}, based on the time instant synchronous speeds are detected, t_{sync}. If the acceleration time is larger than the desired duration, the value of p_{final} is reduced, and if it is shorter the value of p_{final} is increased, according to

$$p_{final,i+1} = p_{final,i} + \mathscr{C}_2(t^*_{sync} - t_{sync}), \tag{19}$$

with $\mathscr{C}_2$ a saturated proportional controller, shown in figure 4 and t^*_{sync} is chosen as $1s$ after t^*_{start}. After each engagement, this learning algorithm updates the value $p_{final,i+1}$ such that the acceleration period converges towards the desired duration.

Equation (19) is an ILC-type learning law similar to (18) for the position model. For the position however, (18) is used to compensate for both variations in travel distance and dynamics, while for the pressure it only compensates for changes in the setpoint while the recursive algorithm of 3.1 compensates for variations in the dynamics.

4. EXPERIMENTAL RESULTS

The developed control strategy has been validated on an experimental test bench, shown in figure 5. It consists of an SOHB TE10 transmission to be controlled, located on the left, driven by an induction motor (30 kW). A secondary SOHB RT20000 transmission combined with a flywheel (2.5 kgm^2) are used to vary the load observed by the controlled transmission. The transferred torque is measured on the setup, but it is only used to illustrate the engagement quality and not for the controllers, as this type of sensor is not available

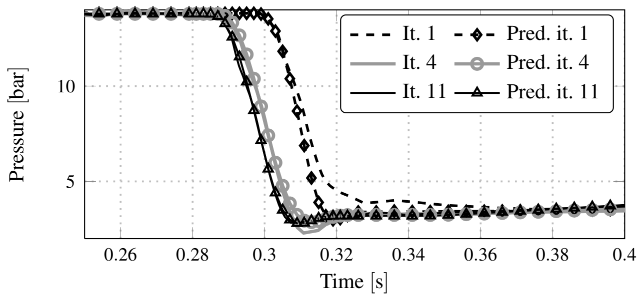

Fig. 6. Measured and predicted pressures: 1st (dashed black), 4th (solid grey), and 11th iteration (solid black).

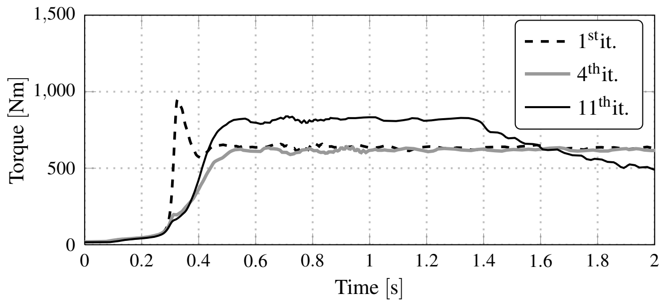

Fig. 7. Measured torques: 1st (dashed black), 4th (solid grey), and 11th iteration (solid black).

in normal transmissions. Only pressure gages measuring the clutch pressures and incremental encoders measuring the shaft rotation speeds are used by the controllers. All experiments are performed with a fixed engine speed, while the output always starts at standstill and is then accelerated by engaging the clutch for first gear in the controlled transmission. These engagements are performed with different observed loads and with different oil temperatures. For the recursive identification, model structure (2) is used with $n_b = 1, n_f = 3$ and $n_k = 2$. The calculations are performed in MATLAB, using MLIB to communicate with a dSPACE 1103 control board.

4.1 Performance analysis

During a first run of experiments the learning process is investigated, while the oil temperature is maintained at 40° C and the load is kept at a constant level. The procedure is initialized by performing a feedforward engagement in order to obtain first estimates for the pressure model and the position model multiplier γ. The first value of the target pressure p_{final} is obtained by choosing a value from the expected range of pressures. After this initialization, the first optimization problem is numerically solved and the learning process starts. The obtained pressure and torques are shown in figures 6 and 7, respectively. These figures show the measured responses to the initial optimized signal (iteration 1), after a few iterations of learning (iteration 4) and after convergence (iteration 11).

During the first iteration a high torque peak is present, making this a poor engagement leading to operator discomfort. After a few iterations, the torque profile becomes more smooth, which is due to the pressure dropping to a low value around $0.31s$, decelerating the piston near the time instant contact with the plates occurs and torque transfer starts. This improves the engagement quality but the remainder of the engagement process takes longer than the desired $1s$. At iteration 11 finally, the pressure profile still drops just around the time torque transfer commences, slowing the piston down before it makes with the plates. Now however, the load is accelerated up to

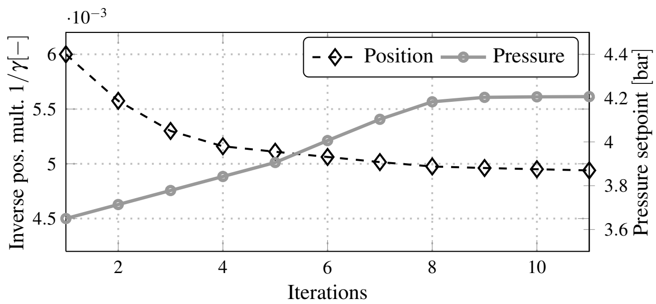

Fig. 8. Evolution of pressure setpoint (black ◇) and $\frac{1}{\gamma}$ (grey ○).

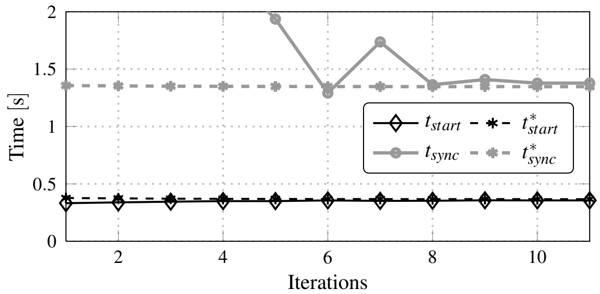

Fig. 9. Evolution of quality indicators t_{start} (solid black ◇) and t_{sync} (solid grey ◇) and their ideal values (dashed $*$).

synchronous speed from $0.35s$ to $1.35s$ in the desired duration of $1s$. The increasingly smooth engagements are due to (i) an improved accuracy of the models for both pressure and position and (ii) convergence of the pressure setpoint.

The accuracy of the pressure model is illustrated in figure 6, where also the predicted pressures are shown. Initially, there is a large difference between predicted and observed behavior. This is partially due to the first model being estimated using data from a feedforward signal that differs from the optimized signal. And as the system behavior is non-linear, the linearized models depend on the control signal. Another cause for the difference is the small amount of available information, as only data from one (short) filling phase can be utilized for the first identification. The recursive identification adapts the models until finally, at iteration 11, the predicted values match the measured ones closely.

The evolution of the position multiplier γ is shown in figure 8. Initially, γ is set too low, such that the predicted positions underestimate the real piston movement. As a result, the piston has already made contact with the plates before the predicted piston starts to slow down. The learning process detects this as an error between t_{start} and t^*_{start}, leading to a correction on γ. After a few iterations the values of γ converge, indicating the convergence of t_{start} to t^*_{start}, such that the position model predicts the time of contact with the plates quite well. As a consequence, the drop in pressure to decelerate the piston occurs at the correct time and the torque profile becomes smoother. Figure 8 also shows the evolution of the pressure setpoint. Initially this setpoint is chosen too low, leading to torque levels that are too low to accelerate the load in the desired timeframe. After a few iterations these values are corrected and converge. Finally, the indicators t_{start} and t_{sync} that are used for the learning of γ and p_{final} are shown in figure 9. The initial error for both is large, with torque transfer starting too soon and synchronous speeds obtained too late. During the learning process both converge towards their targets, such that smooth engagements are obtained.

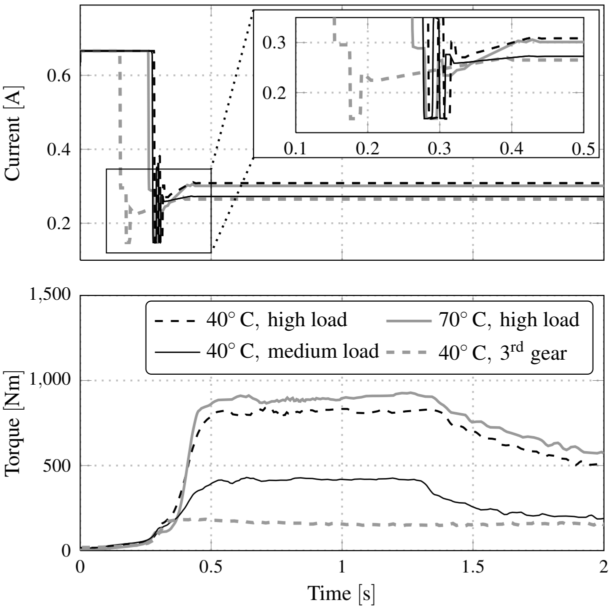

Fig. 10. Control signals and torques for engagements from neutral to 1st gear: high load at 40°C (dashed black), high load at 70°C (solid grey), medium load at 40°C (solid black), and from neutral to 3rd gear (dashed grey).

4.2 Robustness analysis

In order to validate the robustness of the developed control strategy, the cooling is turned off after 11 iterations so the oil temperature gradually increases, and engagements are performed to allow the learning to compensate. Figure 10 compares the performance at iteration 11 with the oil still at 40° C with that obtained with the oil at 70° C. The torque profiles are very similar but the control signal has changed, with the initial high current dropping down earlier. This is due to the reduced oil viscosity, causing the piston dynamics to change as the clutch fills up more easily, which is compensated by a change in γ.

During a second run of experiments, the load is reduced and the learning restarted. The results are also shown in figure 10, after convergence of the learning process. The torque profiles are again similar despite the lower absolute values. This lower torque is required to accelerate the lower load over the same duration of time, and is a result of a lower p_{final}.

It is interesting to note that the converged values of γ and p_{final} obtained in figure 8 are only valid for the initial temperature and load. Generally speaking, variations in oil temperature lead to significant changes in γ, whereas changes in the load result in changes in p_{final}.

A final run of experiments is performed in order to validate the applicability of the proposed strategy. In this case the transition from neutral to first gear is replaced by a transition from neutral to 3rd gear, dramatically increasing the required energy transfer and hence the thermal load of the clutch. To avoid damage due to overheating the learning procedure is therefore restarted with the same parameters, but the desired duration of the acceleration is set to $2s$. The results obtained after convergence are also shown in figure 10, where a similarly smooth start of the torque can be observed. However, because this is another clutch, the control signal itself is quite different.

5. CONCLUSIONS AND FUTURE WORK

This paper presents a two-level, optimization-based learning control strategy for wet clutches. On the low level, the control signal is found by solving a time-optimal control problem. In between the iterations, a high level controller assesses the performance and adjusts the models and constraints, using recursive identification techniques as well as ILC-like update laws. The resulting control strategy learns optimal control signals during normal machine operation and adapts to the operating conditions, avoiding the need for calibrations or complex models. An experimental validation is presented, where the control strategy is successfully applied to minimize the duration of the filling phase, subject to constraints on the engagement quality. In addition, the robustness has been demonstrated by considering variable loads and oil temperatures, as well as applying the controller on different clutches.

Future work will concentrate on extending the method towards the slip phase, to optimize the entire control signal at once.

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